BIOSIGNALS AND COMPRESSION STANDARDS

Leontios J. Hadjileontiadis*

1. INTRODUCTION

Electric, mechanical or chemical signals of biological origin delivered by living things can always be of interest for diagnosis, patient monitoring, and biomedical research. Such biological signals, namely *biosignals*, as electrocardiogram (ECG), electroencephalogram (EEG), surface electromyogram (SEMG), bioacoustic signals (lung, heart, and bowel sounds), are usually presented by large amounts of data when digitized for storage and analysis within a signal processing framework. On the contrary, other medical information, i.e., drug description, demographic and anamnestic data, result in substantially smaller data archives. To this end, it is noteworthy the 80 kbytes data equivalence of 10 sec digitized resting ECG of 8/12 leads to 40 pages of text of an encyclopedic dictionary! (Zywietz, 1998). As a result, data reduction and compression processes are of great interest to biosignal analysis, especially when data transmission (e.g. in telemedicine applications) or long-term recordings (e.g. in sleep laboratories, intensive care) are involved. With appropriate processing of biosignals, the redundant data stream could be reduced to the most significant parameters that could efficiently contribute to medical decision making. In this way, high density storage could be achieved. In the same vein, reduction of the number of bits required to describe a biosignal could facilitate the data transmission, but it must be done with great care if it results in a loss of information. Although new emerging data compression techniques with very promising results are seen in the recent years, some problems have not been entirely addressed. In particular, the following items are still under consideration:

1. The lack of widely adopted compression accuracy standards.
2. The limited number of publicly available benchmark-databases, i.e., accurately acquired, pre-categorized, and standardized biosignals recorded from controls

* Leontios J. Hadjileontiadis, Dept. of Electrical and Computer Engineering, School of Engineering, Aristotle University of Thessaloniki, GR-54124 Thessaloniki, Greece, Tel.: +302310-996340, FAX: +302310-996312, E-mail: leontios@auth.gr.

and patients with various pathologies, for objective testing, evaluation, and performance comparison among the proposed compression techniques.
3. The lack of interoperability of data acquisition and processing equipment of different research groups and/or manufacturers.
4. The difficulty to exchange compressed data between medical databases from different research groups and/or manufacturers because of their incompatibility.

Unfortunately, due to the aforementioned issues, technical barriers to the interconnection of telemedicine centers around the world are set, hampering the use of telemedicine in an economically favorable way, and delaying the development of organizational and healthcare structural adaptations. Standardization in healthcare informatics could contribute to the elimination of these barriers and could provide a dynamic field for organization, coordination, and follow-up of biosignal compression development at a worldwide level. From this perspective, standards and principles that could be applied in the compression process of biosignals, preserving their diagnostic characteristics, are discussed in this chapter.

The rest of the chapter is organized by first covering the categorization and characteristics of the examined biosignals. Section 3 then describes the main compression types. Next, Section 4 refers to the principles and methods used for biosignal compression, while Section 5 gives a telemedical perspective of medical data compression and standardization. Finally, Section 6 concludes the chapter by summarizing the main points of the issues addressed.

2. BIOSIGNALS: CATEGORIZATION AND CHARACTERISTICS

Biosignals, being the acquired output from biological and physical systems, may possess various properties and characteristics that contribute to their diagnostic value. Prior to any analysis, these characteristics must be clearly identified. From the plethora of the available biosignals the following categories and some specific biosignals will be considered in this chapter. In particular:

1. Bioelectric signals, i.e., ECG, EEG, and SEMG.
2. Bioacoustic signals, i.e., lung sounds (LS), heart sounds (HS), and bowel sounds (BS).

These are all noninvasive (recorded from the surface of the human body), one-dimensional biosignals; two-dimensional biosignals, such as X-rays, ultrasound-magnetic resonance-computed tomography images, will not be examined in this chapter. A short description of the characteristics of the examined biosignals follows.

2.1. Characteristics of Bioelectric Signals

2.1.1. Electrocardiogram (ECG)

The ECG is the recording of the electrical activity of the heart, well associated with the mechanical activity of the heart function. In that way, diagnostic analysis of the latter is achieved through the assessment of the ECG. The ECG reflects the temporal changes

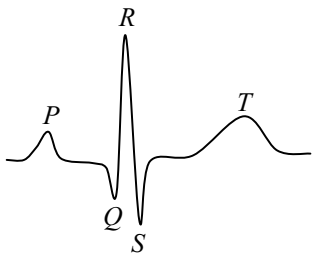

Figure 1. Time domain representation of the important deflections of a typical scalar ECG.

in the electrical potential between pairs of points on the skin surface. In general, its important parts consist of *P, QRS* and *T* waves, shown in Fig. 1. The *P-R* interval is a measure of the time from the beginning of atrial activation to the beginning of ventricular activation, ranging from 0.12 to 0.20 second (Berne and Levy, 1990). The *QRS* complex has duration between 0.06 and 0.10 second and its abnormal prolongation may indicate a block in the normal conduction pathways through the ventricles (Berne and Levy, 1990). The *S-T* interval reflects the depolarization of the entire ventricular myocardium, while the *T* wave its repolarization (Berne and Levy, 1990). The first step in ECG processing is the identification of the *R* wave in order to synchronize consecutive complexes and for *R-R* interval, i.e., heart rhythm, analysis. The latter plays an important role in the heart patient monitoring.

Most of the energy of the ECG is included in the frequency band of 0.05 to 100 Hz (Riggs *et al.*, 1979). Nevertheless, it has been found that the so-called *notches* and *slurs*, superimposed on the slowly varying *QRS* complexes, located in the higher-frequency band of 100 to 1000 Hz, contain additional information (Kim and Tompkins, 1981). In addition, the recording of the electrical field generated by the His and Purkinje activities (Peper *et al.*, 1982) produces a signal in the ECG with an amplitude range of about 1 to 10 μV, useful in the identification of conduction abnormalities. Unfortunately, the low amplitude of this signal makes it comparable to the noise level in the ECG recordings.

2.1.2. Electroencephalogram (EEG)

The EEG is the recording of the electrical activity of the brain, associated with the functioning of various parts of the brain. In routine clinical procedures, the EEG has been used for the diagnosis of epilepsy, head injuries, psychiatric malfunctions, sleep staging/disorders, and others. Usually, it is recorded noninvasively from the scalp by means of surface electrodes. The EEG could reflect both the spontaneous activity of the brain, i.e., the result of the electrical field generated by the brain with no specific task assigned to it, and the evoked potentials, that is, the potentials evoked by the brain as a result of sensory stimulus (e.g. flash lighting and/or audio clicking).

The major power of the EEG is distributed in the range of 0.5 to 60 Hz, although it could be extended into the bandwidth range of DC to 100 Hz, while its amplitude ranges from 2 to 100 μV (Cohen, 1986). The subdivision of the EEG spectrum into fine bands, i.e., the *delta* range (0.5-4 Hz), the *theta* range (4-8 Hz), the *alpha* range (8-13 Hz), and

the *beta* range (13-22 Hz), provides useful diagnostic information in many neurological pathologies (Cohen, 1986).

2.1.3. Surface Electromyogram (SEMG)

Noninvasive measurement of the electrical behavior of the muscle is achieved through the surface EMG (SEMG), recorded by means of surface electrodes placed on the skin overlying the muscle. The SEMG amplitudes depend on the muscle under investigation and the electrodes used, ranging (in normal case) from 50 μV to 5 mV (Cohen, 1986). SEMG can record both voluntary and involuntary muscle activity in addition to the action potentials, produced by external stimulation, such as motor evoked potentials after central or peripheral nerve stimulation (Kimura, 1990). Nevertheless, SEMG has limited spatial resolution, is more susceptible to mechanical artifact, and is more likely to show cross-talk between adjacent muscles than the needle EMG (Pullman *et al.*, 2000).

The useful SEMG spectral content for skeletal muscles lies between 2 to 500 Hz, whereas for smooth muscle between 0.01 to 1 Hz (Cohen, 1986). The characteristics of SEMG can be used as diagnostic tool for kinesiologic analysis of movement disorders; for differentiating types of tremors, myoclonus, and dystonia; for evaluating gait and posture disturbances; and for evaluating psychophysical measures of reaction and movement time (Pullman *et al.*, 2000).

2.2. Characteristics of Bioacoustic Signals

2.2.1. Lung Sounds (LS)

The LS refer to the sounds produced by the structures of the lungs during breathing, usually examined by auscultation (listening) with a stethoscope. When listening to the lungs, the categories of findings include *normal* breath sounds and *abnormal* breath sounds (Kraman, 1983).

Normal LS occur in all parts of the chest area, including above the collarbones and as low as the bottom of the rib cage. In particular, they are categorized as: *tracheal* LS (heard over the trachea having a high loudness and a wide frequency band of 0-2kHz); *vesicular* LS (heard over dependent portions of the chest, not immediate proximity to the central airways, within a frequency band of 0-600 Hz); *bronchial* LS (heard in the immediate vicinity of central airways, but principally in the trachea and larynx); *bronchovesicular* LS (resembling the character between vesicular LS and bronchial LS, heard at intermediate locations between the lung and the large airways); and *normal crackles* (inspiratory LS heard over the anterior or the posterior lung bases).

There are several types of abnormal breath sounds: *rales*, *rhonchi*, and *wheezes* are the most common. Wheezing can sometimes be heard without a stethoscope, and other abnormal sounds are sometimes also loud enough to be detected with the unaided ear. Rales (crackles or crepitations) are small clicking, bubbling, or rattling sounds in a portion of the lung. They are believed to occur when air opens closed alveoli (air spaces) and they are further categorized to *fine* and *coarse* crackles (Kraman, 1983). Rales may be further described as moist, dry, fine, and coarse, among other descriptors. Rhonchi are sounds that resemble snoring. They are produced when air movement through the large

airways is obstructed or turbulent. Wheezes are high-pitched (200-800 Hz) musical sounds produced by narrowed airways, often occurring during expiration.

For getting the full frequency range and electrical signals that can be processed, microphones, i.e., electronic stethoscopes, are used, with an almost flat response in the frequency range from 20 Hz to 5 kHz. The variety in the categorization of LS implies changes in the acoustic characteristics either of the source and/or the transmission path of the LS inside the lungs, due to the effect of a certain pulmonary pathology; hence, time and frequency characteristics of the LS signals reflect these anatomical changes and serve as diagnostic tools (Gavriely and Cugell, 1994; Hadjileontiadis *et al.*, 2002).

2.2.2. Heart Sounds (HS)

Heart sounds are defined as the repetitive "lub-dub" sounds of the beating of the heart (Gavriely and Cugell, 1994), categorized to: *first heart sound* (or S_1), considered as normal HS, occurs at the beginning of ventricular systole when ventricular volume is maximal, and lasts about 100 to 120 msec (Cohen, 1986); *second heart sound* (or S_2), also considered as normal HS, occurs at the end of ventricular systole; *third heart sound* (or S_3 or "S_3 gallop"), occurs just after the S_2 as a result of decreased ventricular compliance or increased ventricular diastolic volume, it is a low-frequency (20 to 70 Hz) transient with low amplitudes, lasts about 40 to 50 msec (Cohen, 1986), and serves as a sign of congestive heart failure; *fourth heart sound* (or S_4 or "S_4 gallop"), occurs at the time of atrial contraction, is similar to S_3 in duration and bandwidth, and it denotes ventricular stress. Additional heart malfunctions and reflected through the abnormal HS that include changes in intensity of normal HS, splitting of sound components, *ejection clicks* and sounds, *opening snaps*, and *murmurs* (systolic and diastolic) (Cohen, 1986).

Over the 95% of the acoustic energy of S_1 and 99% of the one of S_2 is concentrated under 75 Hz. There is decay in the average spectrum after its peak at 7 Hz containing one or more shallow and wide peaks ending at 150 Hz (Arnott *et al.*, 1984). In a similar vein, the frequency content of most cardiac murmurs is also in the low range (Gavriely and Cugell, 1994), but in some cases is extended, overlapping the low-frequency part of LS.

2.2.3. Bowel Sounds (BS)

Bowel sounds refer to the sounds heard when contractions of the lower intestines propel contents forward (On-line Medical Dictionary, 1997). Unfortunately, there is no reference of what can be considered normal bowel sound activity, thus, only subjective description of the acoustic impression of normal BS exists, employing terms such as "rushes" or "gurgles". Nevertheless, time and frequency domain characteristics of BS could be used as a means for defining normal BS. In particular, BS with frequency content in the range of 100-1000 Hz, with durations within a range of 5-200 msec, and with widely varying amplitudes, could be characterized as *normal* BS (Bray *et al.*, 1997). The "staccato" character seen in many BS of the colon corresponds to frequencies within 500 to 700 Hz and time durations within 5 to 20 msec (Bray *et al.*, 1997). Moreover, differences in the sound-to-sound intervals of BS from different pathologies, i.e., irritable bowel syndrome, Crohn's disease, and from controls, establish a time-domain tool for associating changes in the BS characteristics with bowel pathology (Craine *et al.*, 2001).

Advanced signal processing of BS could reveal more diagnostic features of BS from bowel pathologies (Hadjileontiadis *et al.*, 2002).

3. COMPRESSION TYPES

Compression processes, whether they operate on audio, video, images, or a random collection of files, are categorized into two basic types: *lossless* and *lossy*. In the lossless processes the original data can be *exactly* reconstructed from their compressed form, while in the lossy ones only an *approximation* of the original data can be retrieved. In that way, in the lossless compression all information is saved and the compression is reversible. On the contrary, in lossy compression some information is "thrown away" based on the perceptual response of an observer, hence, the compression is irreversible.

Lossless compression is typically adopted for text compression, while lossy for images and sound where a little bit of resolution loss is often undetectable or, at least, acceptable. It is noteworthy the abstract sense of the term "lossy", since it does not imply random lost data, but instead refers to a loss of a quantity, such as a frequency component, or to the loss of noise. In that way, although lossy compression involves a kind of information loss, it is critical to see if the "authentic meaning", in our case the diagnostic feature of the compressed biosignal, is fully maintained, or even improved, after compression.

The structure of both lossless and lossy compression algorithms always involves two basic components, i.e., the *model* and the *coder*. The model component detects any possible bias on the input data, i.e., any unbalanced probability distribution over the input data, by knowing or discovering something about the structure of the input. In that way, the coder component takes under consideration the probability biases captured by the model in order to effectively generate codes. The latter is achieved by lengthening low-probability data and shortening high-probability ones. There are many different ways to design the model component of compression algorithms with various degrees of sophistication. Nevertheless, the coder components tend to be quite generic, such as, for the case of lossless compression, Huffman (Huffman, 1952), Lempel-Ziv-Welch (LZW) (Welch, 1984) or arithmetic codes (Moffat *et al.*, 1998). The Huffman code maps fixed length symbols to variable length codes and it is optimal only when symbol probabilities are powers of 2. In its adaptive form, an *a priori* estimation of probabilities is not needed. The LZW is a dictionary-based code that maps a variable number of symbols to a fixed length code. The arithmetic code uses a variable number of bits for data encoding according to the probability assigned to the encoded symbol. Low probability symbols use many bits, while high probability symbols use fewer bits. This makes arithmetic coding sound very similar to Huffman coding. However, an arithmetic encoder does not have to use an integral number of bits to encode a symbol. For example, if the optimal number of bits for a symbol is 2.4, a Huffman coder will probably use 2 bits per symbol, whereas the arithmetic encoder my use very close to 2.4. This means that an arithmetic coder can usually encode data using fewer bits.

Table 1. Most common lossless and lossy compression techniques/standards

Lossless	Lossy
Huffman	Scalar Quantization (Uniform/Non-uniform)
Adaptive Huffman	Vector Quantization
Lempel-Ziv 77 (LZ77)/LZSS	Differential or Predictive
LZ-Welch (LZW)	Transform Coding (Discrete Cosine, Polynomial,
LZ-Oberhumer (LZO)	Wavelet)
Run-Length Encoding (RLE)	JPEG
Arithmetic	MPEG
Burrows Wheeler	MP3/AAC
	Fractal Compression
	Model-based Compression

As far as lossy compression is concerned, the most common coding techniques include mapping of regions of a data set onto elements of a smaller one (scalar quantization); mapping of multidimensional space into a smaller set of data (vector quantization); transform of the input into a different form that can then either be compressed better or for which we can more easily drop certain terms without as much qualitative loss in the output (transform coding); association of a family of functions, which have fixed points that may be found in an iterative way without unduly long convergence, with data point values (fractal compression); and characterization of the source data in terms of an underlying model so the entire system is described by only a few bytes of parameter data (model-based compression). JPEG, MPEG and MP3/AAC are widely applied compression standards that are used for still images (JPEG), videos (MPEG), and audio (MP3/AAC) compression. All of these standards combine many compression techniques, including Huffman, arithmetic, residual, run-length, scalar quantization, transform, and model-based (psychoacoustic) coding.

The aforementioned lossless and lossy compression techniques/standards are summarized in Table 1. More details can be found in Moffat's and Turpin's book (2002) and at the Data Compression Info (2002). The comparison of the quality of one versus another compression algorithm depends on the type of the algorithms. Criteria like the compression time, the reconstruction time, the size of the compressed data, and the degree of generality, could be easily adopted in the comparison among lossless compression algorithms (ACT, 2002). Nevertheless, these criteria should be revised under the perspective of the "degree of goodness" of the lossy approximation. In that case, tradeoffs between the amount of compression, the runtime, and the quality of reconstruction are involved, varying in significance according to the application and the signal characteristics. This is clearly described in the following Section.

4. BIOSIGNAL COMPRESSION: PRINCIPLES AND METHODS

Biosignal compression requires deep consideration of the signal properties in order to achieve both successful compression and accurate representation of the signal diagnostic features. To this end, bioelectric and bioacoustic data compression should be handled differently than image or speech data compression, since more constrains are imposed by the former case. This is due to the property of the human eye or ear to act as

a smoothing filter, permitting a certain amount of tolerance for distortion with the image and speech data, where with the bioelectric and bioacoustic signals, not only should the overall distortion be low, but, in addition, its essential areas/characteristics (as they are described in Section 2) need to be preserved with the highest possible morphologic fidelity for accurate representation of the diagnostic information. From this perspective, visual inspection of the reconstructed biosignal after compression and/or transmission should also be included in the assessment of the quality of reconstruction, especially when noise contamination is present.

4.1. Principles

The basic principles that apply in the case of biosignal compression are (Zywietz, 1998):

1. Adoption of correct evaluation criteria.
2. Bandwidth limitation and sampling rate reduction.
3. Redundancy reduction.
4. Information reduction

These principles, when followed by efficient signal processing methods, lead to enhanced biosignal compression.

4.1.1. Evaluation Analysis Criteria

The main points in the evaluation analysis of biosignal compression are: *error figures* estimation, computation of *expenditure for encoding/decoding procedures*, consideration of *stability versus transmission errors*, *archive transportability, scalability, standardization*, and *encryption* (Zywietz, 1998).

Focusing on error figures, the most common ones (listed in Table 2), are based on the differences between the N-sample original biosignal, $S(k)$ and the reconstructed, $\hat{S}(k)$, with k=1,…,N. Usually, more than one error type should be used in the evaluation of the biosignal compression procedure, since absolute errors may be as misleading as *RMSE* figures (see Table 2) (Zywietz, 1998). For instance, if a large absolute error occurs *between* events of interest, such as successive *PQRST* complexes in ECG, it may result in negligible affection of the reconstructed signal quality, from a diagnostic point of view. Moreover, small *RMS* figures may be misleading when mean squared differences are small but large differences appear in diagnostically relevant short periods of the signal, such as at the location of explosive bioacoustic signals (crackles or sound bursts) or the QRS complex in ECG. According to Zywietz (1998), a *peak amplitude related error* (absolute or in prevent of a maximum amplitude to be measured), and an *RMSE figure* are the two principal error figures that should be used in biosignal compression. Like *RMS* figures, the *SNR* (see Table 2) often smoothes out large local errors; the *PRMSD* (see Table 2) is preferred for the validation of the reconstruction of a zero-mean signal. In any case, error figures have to be handled with caution.

4.1.2. Bandwidth Limitation and Sampling Rate Reduction

Before embarking for biosignal compression it is important to consider issues like bandwidth limitation and sampling rate reduction. According to the Nyquist criterion, the sampling frequency should be at least two times the upper frequency of the signal in order to avoid spectrum aliasing. Nevertheless, this upper frequency does not always correspond to the diagnostic parts of the recorded biosignal, but, instead, to the superimposed noise. In that case, the "useful" bandwidth, i.e., the frequency range within the spectrum of the diagnostically useful signal lies (see biosignals frequency characteristics in Section 2), could be shortened and the sampling frequency could be reduced accordingly (refer to Zywietz *et al.* (1983) for an example in the case of ECG).

Table 2. Most common error figures used in compression evaluation

Name	Definition[a]
Local Absolute Error (LAE)	$LAE(k) = \mid S(k) - \hat{S}(k) \mid$
Max Absolute Error (MAE)	$MAE(k) = \max\{\mid S(k) - \hat{S}(k) \mid\}$
Peak Amplitude Related Error (PARE)	$PARE(k) = [S(k) - \hat{S}(k)] / \max\{S(k)\}$
Normalized Maximum Amplitude Error (NMAE)	$NMAE = \max\{\mid \mathbf{S} - \hat{\mathbf{S}} \mid\} / [\max\{\mathbf{S}\} - \min\{\mathbf{S}\}]$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\{\sum_{i=1}^{N} [S(k) - \hat{S}(k)]^2\} / N}$
Percentile Root Mean Square Difference (PRMSD)	$PRMSD = 100 \cdot \sqrt{\{\sum_{i=1}^{N} [S(k) - \hat{S}(k)]^2\} / \{\sum_{i=1}^{N} S^2(k)\}}$
Signal-to-Noise Ratio (SNR)	$SNR \sum 10 \log\{\sum_{i=1}^{N} [S(k) - \overline{S}]^2 / \sum_{i=1}^{N} [S(k) - \hat{S}(k)]^2\}$

[a] $\boldsymbol{S}$, $\hat{\boldsymbol{S}}$, and $\overline{S}$ denote the N-sample original biosignal vector, the reconstructed one, and the mean value of $\boldsymbol{S}$, respectively; k=1,…,N.

4.1.3. Redundancy Reduction

Data redundancy in biosignals could be seen in the form of *intersample correlation*, i.e., no statistical independence exists between neighboring samples, and *unequal probability* in the occurrence of the quantized signal amplitudes. The first form of redundancy could be reduced by using first or second order differences between the samples (Zywietz, 1998), resulting in significant shortened digital word lengths per sample. For reducing the second form of redundancy, mostly in the data transmission case, (adaptive) Huffman coding (see Section 3), which assigns shortest and longer codes to digital words with highest and lower probabilities, respectively, or other lossless compression types could be employed (see Table 1).

4.1.4. Information Reduction

Based on the biosignal characteristics, efficient reduction of the "useful" information can be achieved, when appropriate mapping and/or transform is applied to the original signal. For instance, the ECG could be mapped to straight lines (curves are approximated by straight line segments), slopes and plateaus, resulting in an approximation of the original signal with a stepped function that occupies less information. Based on this perspective, lossy ECG compression schemes have been proposed in the literature (Abenstein and Tompkins, 1982; Ishijiama *et al.*, 1983), reporting compression ratios within the range of 2:1-10:1, using predefined accuracy levels. Transform coding reduces the biosignal information by transforming an *N*-sample block into a set of transform coefficients. Characteristic examples of transforms applied in biosignals compression are: *Karhunen-Loeve transform* or *Principal Component Analysis* (PCA), which is based on the eigenvectors derived from the signal characteristics and represent "typical" sequences of the input data set for a given *RMSE* (Elliot and Rao, 1982); *Discrete Cosine transform*, where the signal is represented by a set of cosines; and *Discrete Wavelet transform*, where the signal is represented by a set of wavelets (Gholam *et al.*, 1998).

4.2. Methods

For illustrating the implementation of the aforementioned principles in biosignal compression, a short description of sample compression schemes applied to biosignals follows. The methods are categorized according to the processed biosignal type.

4.2.1. ECG Data Compression

The ECG data compression problem has been widely addressed by many research groups, resulting in many different compression algorithms, mainly categorized to *parameter extraction techniques*, which retain the parameters/characteristics of ECG, *direct time-domain techniques*, such as amplitude zone time epoch coding, delta, and entropy coding, and *transform-domain techniques* (see §4.1.4).

One interesting subcategory of such algorithms employs neural networks (Nazeran and Behbehani, 2000). Although PCA (see §4.1.4) results in uncorrelated transform coefficients (diagonal covariance matrix) and minimizes the total entropy compared with any other transform (Elliot and Rao, 1982), it requires the computation of the eigenvectors of the correlation matrix of the ECG data set, which, usually is a very large matrix. By employing a multiple Hebbian neural network, Al-Hujazi and Al-Nashash (1996), reduced the computational load of the PCA for arbitrary size of the ECG input vector. In this way, they achieved a compression ratio (*CR*) up to 30 with a *PRMSD* of 5%, using data from the MIT/BIH ECG arrhythmia database (MIT/BIH ECG, 2002) and a training set with all expected arrhythmias. By using autoassociative neural network, where the input and output patterns are the same, Hamilton *et al.* (1995), proposed an ECG compression scheme. The underlying idea was the fact that the majority of beats within a given recording ECG segment have the same gross morphology. Consequently, a compression capability could be established by storing an average waveform and compressing the difference only. They achieved a *CR* of 10 with a *PRMSD* of 4.6%, for a network size of 360-30-360 (Hamilton *et al.*, 1995). Vector quantization (see Section 3)

involves the creation of a codebook of vectors that best spans the data of interest. A Kohonen neural network-based adaptation of the codebook vectors according to distance measurements and time changes was proposed by McAuliffe (1993). The resulted *CR* ranged from 3:1 to 19:1, according to the heart rate and noise content.

Another significant subcategory includes ECG compression schemes that use interbeat correlation between ECG cycles. In particular, long-term prediction (Nave and Cohen, 1993) and average beat subtraction (Hamilton and Tompkins, 1991) are structured on beat-to-beat correlation. However, several limitations of these methods have been reported by Ramakrishnan and Saha (1997), who used the interbeat correlation combined with period-and-amplitude-normalized and discrete-wavelet-transform truncation, for achieving redundancy-free original ECG data. In this way, *CR*s ranging from 13.4:1 to 19.1:1 with *PRMSD* values ranging from 9.9% to 13.3% were found. An enhancement of this approach was proposed by Istepanian *et al.* (2001), where higher-order statistics-based criteria and modeling were applied to the wavelet-transform domain, resulting in higher *CR*s (11:1-31.5:1) and smaller *PRMSD* values (1.74%-12.9%). A telemedical application of the latter algorithm, combined with adaptive arithmetic coding, is presented in Section 5. In the same vein, Wei *et al.* (2001), have combined the interbeat correlation of ECGs with the quasi-periodic analysis of the truncated singular value decomposition technique to decompose an ECG sequence into a linear combination of a set of basic patterns with associated scaling factors, producing high compression results (Wei *et al.*, 2001).

Furthermore, ECG data compression by parametric modeling of the discrete cosine transformed ECG signal, using separate modeling of low and high frequency regions of the transformed signal, achieves a *CR* of 40:1 with *PRMSD* values of 5% to 8% (Madhukar and Murthy, 1993). Finally, a lossy ECG data compression scheme that uses an adapted LZ77 algorithm (see Section 3) to code detected repetitions in the ECG data results in *CR*s of 9.2:1 to 13.4:1 and *PRMSD* values of 0.44% to 0.64% (Horspool, 1995).

4.2.2. EEG Data Compression

Both lossless and lossy EEG data compression methods have been exploited in the literature. With regard to the lossless one, the most widely known methods employ repetition count, Lempel-Ziv coding, Huffman coding, vector quantization, and techniques based on signal predictors, such as Markov predictor, digital filtering predictor, (adaptive) linear predictor, maximum likelihood, artificial neural networks (Antoniol and Tonella, 1997). Nevertheless, dictionary-based techniques (LZ77, LZ78) do not work well when applied to the EEG data, since their efficiency is based on the exploitation of the frequent reoccurrence of certain exact patterns detected in the data, a principle that does not apply in the nondeterministic nature of the EEG signal. Using the EEG knowledge, compression can be enhanced by removing redundancy, in terms of statistical dependence between samples. Time dependence, exploited by the prediction methods, can lead to the estimation of the next sample from the previous ones by adding some delay inputs to the predictor, while spatial dependence between input EEG channels can be captured by lossless methods based on multivariate time series analysis (Cohen *et al.*, 1995), and vector quantization (Antoniol and Tonella, 1997). In the latter, the input EEG channels (or derivatives) samples are mapped to a code vector and encoding is performed only to the error vector. A detailed comparison of the performance of the

lossless EEG compression techniques can be found in the work of Antoniol and Tonella (1997). Although lossy EEG data compression can yield significantly higher compression ratios, while potentially preserving the diagnostic accuracy, it is not usually employed due to legal concerns. Instead, near-lossless EEG compression is preferred, since it gives quantitative bounds on the errors introduced during compression. In that way, the error is controlled and the precious bandwidth is utilized more efficiently. Memon *et al.* (1999), proposed a context-based trellis-searched delta pulse code modulation technique that satisfies a near-lossless error criterion by minimizing the entropy of the quantized prediction error sequence derived from an autoregressive model.

4.2.3. SEMG Data Compression

Unlike ECG and EEG, only a limited number of SEMG compression techniques have been reported in the literature. Among them, Guerrero and Mailhes (1997) compares widely employed compression methods, such as differential pulse code modulation, multi pulse coding, and code excited linear predictor coding, with techniques based on transforms for SEMG data compression. They propose the encoding of the wavelet coefficients using a four-level multiresolution decomposition scheme, as the one that provides the best results (Guerrero and Mailhes, 1997). An extension to this was proposed by Wellig *et al.* (1998), who used embedded zero-tree wavelet encoding for compressing SEMG data rapidly and with little distortion (*PRMSD* values of 1% to 10%).

It is noteworthy that when muscle fatigue occurs, SEMG bandwidth limitation (see §4.1.2) could be achieved, due to decreasing muscle fiber conduction that results in spectral compression of the SEMG signal (Lindstrom and Magnusson, 1977). From this perspective, Lowery *et al.* (2000), proposed a spectral distribution technique that captures the compression of the SEMG power and amplitude spectra by calculating the mean shift in all percentile frequencies throughout the entire spectrum, providing an efficient way to define the "useful" upper frequency that results in sampling frequency reduction (see §4.1.2).

4.2.4. LS, HS, and BS Data Compression

Similarly to the SEMG case, compression of bioacoustic data is limited in the literature. Usually, data reduction-based methods are preferred in order to eliminate the undesired signal, i.e., noise, resulting in less data that need encoding. To this vein, several de-noising algorithms have been proposed that separate LS, HS, and BS from the noisy background, based on their transient (nonstationary) characteristics (see §2.2). A thorough description of these algorithms can be found in Hadjileontiadis *et al.* (2002). Most of them employ wavelet transform, fuzzy logic, and higher-order statistics. An alternative way of data reduction that performs fractal dimension analysis of the bioacoustic signals, capturing their changes in complexity, results in high data reduction percentages in a very fast and efficient way (Hadjileontiadis and Rekanos, 2003). For further modeling and analysis of bioacoustic signals the reader should refer to the ILSA database (ILSA, 2002).

5. FROM A TELEMEDICAL PERSPECTIVE

The introduction of telematics in health care has emphasized the need for organized standardization and for a common use of medical informatics and telematics standards. Regarding compression, the International Telecommunication Union (formerly CCITT) Telecommunications Standardization sector (ITU-T) has the responsibility for compression techniques applied to audio and visual communications, i.e., voice audio and speech codecs, and multimedia terminals (ICU-T, 2002). The ITU-T compression standards recommendation includes the JPEG and MPEG standards for image and video compression, respectively (ICU-T, 2002).

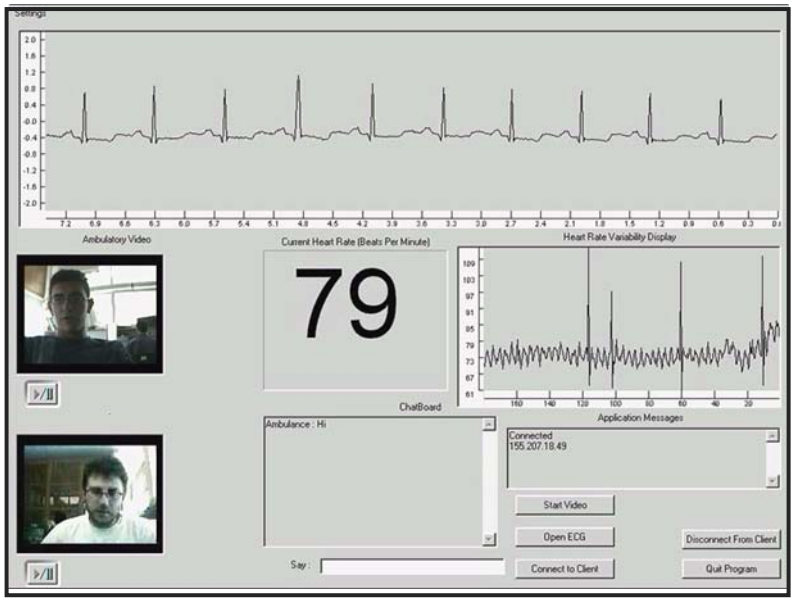

Figure 2. The CardiOTElelink interface (Panoulas, 2002), for mobile transmission of ambulatory ECG.

Regarding the interoperability of the telemedical systems, the Digital Imaging and Communications in Medicine (DICOM) standard, a standard network interface and standard model for imaging devices that can facilitate information systems integration, has been proposed (DICOM, 2002). DICOM is a complex set of documents that provide detailed definition of a rich set of communication services and associated protocols based on an object model that represents an abstraction of certain aspects of the real world. By simply specifying which DICOM functions are supported, different manufacturers could claim conformance, hence, their telemedical products could be applicable to networked environments.

Technological advantages in wireless communications, in recent years, have put into focus wireless biomedical data transmission, giving rise to mobile telemedicine. This perspective appreciates the role of the compression techniques described so far, since bandwidth limitations in mobile telecommunications could be circumvented with

efficient compression. An example of a mobile telemedical system for ECG data is presented in Fig. 2. This is a mobile telemedical framework, namely CardiOTElelink (Panoulas, 2002), which uses public wireless cellular data lines (GSM-28.8 kbps up/download) to transmit video and patient biosignals from a moving ambulance to a receiving physician at the basestation-hospital (Panoulas, 2002). The compression scheme adopted by the CardiOTElelink is the one proposed by Istepanian *et al.* (2001). It results in high compression ratios (*CR*s over 20:1 with *PRMSD* values below 2.5%) that allow real-time transmission of ECG data, patient/physician videos (5 frames/sec), heart beat, heart rate variability, full-duplex voice, and text messages (Panoulas, 2002). Other, currently emerging, mobile protocols, such as Bluetooth, Wi-Fi, GPRS, 3GSM, allow wider exploitation of mobile telemedical applications and provide an ample space for new compression techniques.

6. CONCLUSIVE COMMENTS

Compression of biological data remains an important issue, despite the vast increase in storage capacity and transmission speed in communication pathways. This is due to their diagnostic characteristics, which set a common endeavor to all compression approaches, i.e., efficient biosignal data compression yet unaffected diagnostic characteristics. To address this challenge, many customized lossless and lossy techniques have been proposed so far, which reduce data redundancy, employ signal approximation or apply signal transforms towards higher compression ratios and smaller reconstruction errors. Nevertheless, adoption of different data sets and/or evaluation criteria makes their comparison difficult. By reviewing the characteristics of biosignals, the compression types, the main principles, and the most applied methods in biosignals compression, this chapter has tried to enlighten the framework wherein forthcoming compression schemes could blossom.

7. REFERENCES

Abenstein, J., and Tompkins, W., 1982, A new data reduction algorithm for real-time ECG analysis, *IEEE Trans. on Biomed. Eng.* **29**(1):43-48.

ACT: Archive Comparison Test, 2002; http://compression.ca.

Al-Hujazi, E., and Al-Nashash, H., 1996, ECG data compression using Hebbian neural networks, *J. Med. Eng. Technol.* **20**(6):211-218.

Antoniol, G., and Tonella, P., 1997, EEG data compression techniques, *IEEE Trans. on Biomed. Eng.* **44**(2):105-114.

Arnott, P. J., Pfeiffer, G. W., and Tavel, M. E., 1984, Spectral analysis of heart sounds: relationships between some physical characteristics and frequency spectra of first and second heart sounds in normals and hypertensives, *J. Biomed. Eng.* **6**(2):121-128.

Berne, R. M., and Levy, M. N., 1990, Cardiovascular system, in: *Principles of Physiology*, R. M. Berne, and M. N. Levy, eds., Wolfe Publications Ltd, London, pp. 212-213.

Bray, D., Reilly, R. B., Haskin, L., and McCormack, B., 1997, Assessing motility through abdominal sound monitoring, in: *Proc. 19th Int. Conf. IEEE/EMBS*, B. Myklebust, and J. Myklebust, eds., IEEE Press, Chicago, IL, pp. 2398-2400.

Cohen, A., 1986, *Biomedical Signal Processing-Volume II: Compression and Automatic Recognition*, CRC Press, Boca Raton, FL, pp. 113-137.

Craine, B. L., Silpa, M. L., and O'Toole, C. J., 2001, Enterotachogram analysis to distinguish irritable bowel syndrome from Crohn's disease, *Dig. Dis. and Sciences* **46**(9):1974-1979.

Data Compression Info, 2002; http://datacompression.info/Tutorials.shtml.
DICOM: Digital Imaging and Communications in Medicine, 2002; http://medical.nema.org.
Elliot, D. F., and Rao, K. R., 1982, *Fast Transforms, Algorithms, Analysis and Applications*, Academic Press, New York.
Gavriely, N., and Cugell, D. W., 1994, *Breath Sounds Methodology*, CRC Press, Boca Raton, FL.
Gholam, H. H., Nazeran, H., and Moran, B., 1998, ECG compression: evaluation of FFT, DCT, and WT performance, *Australasian Physical & Eng. Sciences in Medicine* **21**(4):186-192.
Guerrero, A., and Mailhes, C., 1997, On the choice of an electromyogram data compression method, *Proc. of 19th IEEE EMBS* **4**:1558-1561.
Hadjileontiadis, L. J., and Rekanos, I. T., 2003, Detection of explosive lung and bowel sounds by means of fractal dimension, *IEEE Signal Processing Letters* (in press).
Hadjileontiadis, L. J., Tolias, Y. A., and Panas, S. M., 2002, Intelligent system modeling of bioacoustic signals using advanced signal processing techniques, in: *Intelligent Systems: Technologies and Applications – Vol. III: Signal, Image, and Speech Processing*, C. T. Leondes, ed., CRC Press, Boca Raton, FL, chap. 3, pp. III 103-156.
Hamilton, D. J., Thomson, D. C., and Sandham, W. A., 1995, ANN compression of morphologically similar ECG complexes, *Med. Biol. Eng. Comput.* **33**(6):841-843.
Hamilton, P. S., and Tompkins, W. J., 1991, Compression of the ambulatory ECG by average beat subtraction and residual differencing, *IEEE Trans. on Biomed. Eng.* **38**(3):253-259.
Horspool, R. N., 1995, ECG data compression using Ziv-Lempel techniques, *Computers and Biomedical Research* **28**:67-86.
Huffman, D. A., 1952, A method for the construction of minimum-redundancy codes, *Proceedings of the I.R.E.* **40**(9):1098-1101.
ILSA: International Lung Sounds Association, 2002; http://www.ilsa.cc.
Ishijiama, M., Castelli, A., Combi, C., Pinciroli, F., 1983, Scan-along polygonal approximation for data compression of electrocardiograms, *IEEE Trans. on Biomed. Eng.* **30**(11):723-729.
Istepanian, R. S. H., Hadjileontiadis, L. J., and Panas, S. M., 2001, ECG data compression using wavelets and higher-order statistics, *IEEE Trans. on Information Tech. in Biomedicine* **5**(2):108-115.
ITU-T: International Telecommunication Union Telecommunications Standardization sector, 2002; http://www.itu.int/home.
Kim, Y., and Tompkins, W. J., 1981, Forward and inverse high frequency ECG, *Med. Biol. Eng. Comp.* **19**:11.
Kimura, J., 1990, *Electrodiagnosis in Diseases of Nerve and Muscle: Principles and Practice*, F. A. Davis, Philadelphia.
Kraman, S. S., 1983, *Lung Sounds: An Introduction to the Interpretation of Auscultatory Findings*, American College of Chest Physicians, Northbrook, IL, pp. 14-21.
Lindstrom, L. H., and Magnusson, R. I., 1977, Interpretation of myoelectric power spectra: a model and its applications, *Proc. IEEE* **65**:653-662.
Lowery, M. M., Vaughan, C. L., Nolan, P. J., and O'Malley, M. J., 2000, Spectral compression of the electromyographic signal due to decreasing muscle fiber conduction velocity, *IEEE Trans. on Rehabilitation Eng.* **8**(3):353-361.
Madhukar, B., and Murthy, I. S. N., 1993, ECG data compression by modeling, *Computers and Biomedical Research* **26**:310-317.
McAuliffe, J. D., 1993, Data compression of the exercise ECG using a Kohonen neural network, *J. Electrocardiol.* **26**(Suppl):80-89.
Memon, N., Kong, X., and Cinkler, J., 1999, Context-based lossles and near-lossless compression of EEG signals, *IEEE Trans. on Information Tech. in Biomedicine* **3**(3):231-238.
MIT/BIH ECG: Massachusetts Institute of Technology/Beth Israel Hospital ECG Database, 2002; http://ecg.mit.edu.
Moffat, A., and Turpin, A., 2002, *Compression and Coding Algorithms*, Kluwer Academic Publishers, Boston.
Moffat, A., Neal, R., and Witten, I. H., 1998, Arithmetic coding revisited, *ACM Trans. on Information Systems* **16**(3):256-294.
Nave, G., and Cohen, A., 1993, ECG compression using long-term prediction, *IEEE Trans. on Biomed. Eng.* **40**(9):877-885.
Nazeran, H., and Behbehani, K., 2000, Neural networks in processing and analysis of biomedical signals, in: *Nonlinear Biomedical Signal Processing-Volume I: Fuzzy Logic, Neural Networks, and New Algorithms*, M. Akay, ed., IEEE Press, New York, NY, pp. 89-91.
On-line Medical Dictionary, Academic Medical Publishing & CancerWEB, 1997; http://cancerweb.ncl.ac.uk/cgi-bin/omd?bowel+sounds.

Panoulas, C., 2002, *ECG data processing and compression for transmission through wireless cellular networks*, Diploma Thesis, Dept. of Electrical and Computer Eng., Aristotle Univ. of Thessaloniki, Greece.

Peper, A., Jonges, R., Losekoot, T. G., and Grimbergen, C., 1982, Separation of His-Purkinje potentials from coinciding atrium signals: removal of the P-wave from electrocardiogram, *Med. Biol. Eng. Comp.* **20**:195.

Pullman, S. L., Goodin, D. S., Marquinez, A. I., Tabbal, S., and Rubin, M., 2000, Clinical utility of surface EMG, *Neurology* **55**:171-177.

Ramakrishnan, A. G., and Saha, S., 1997, ECG coding by wavelet-based linear prediction, *IEEE Trans. on Biomed. Eng.* **44**(12):1253-1261.

Riggs T., Isenstein, B., and Thomas, C., 1979, Spectral analysis of the normal ECG in children and adults, *J. Electrocardiol.* **12**(4):377.

Wei, J.-J., Chang, C.-J., Chou, N.-K., and Jan, G.-J., 2001, ECG data compression using truncated singular value decomposition, *IEEE Trans. on Information Tech. in Biomedicine* **5**(4):290-299.

Welch, T. A., 1984, A technique for high performance data compression, *IEEE Computer* **17**(6):8-19.

Wellig, P., Cheng, Z., Semling, M., and Moschytz, G. S., 1998, Electromyogram data compression using single-tree and modified zero-tree wavelet encoding, *Proc. of 20th IEEE EMBS* **3**:1303-1306.

Zywietz, C., 1998, Criteria for data compression of biosignals and methods for data reduction in electrocardiography, in: *Biotelemetry XIV: Proceedings of the XIV International Symposium on Biotelemetry-Chapter 7: ECG Monitoring and Processing*, T. Penzel, S. Salmons, and M. R. Neuman, eds., Tectum Verlag, Marburg, pp. 281-292.

Zywietz, C., Palm, C., Spitzenberger, U., Wetjen, A., 1983, A new approach to determine the sampling rate for ECGs, in: *Computers in Cardiology*, K. Ripley, ed., IEEE Computer Society Press, Los Alamitos, CA, pp. 261-264.